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VISION-BASED INSPECTION OF BOLTED JOINTS: FIELD EVALUATION ON A HISTORICAL TRUSS BRIDGE IN VIETNAM

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Abstract. Vision-based inspection has received significant interests from structural health monitoring and maintenance academia. The vision-based approach has unique advantages over the traditional sensor-based inspection, including non-contact sensing, low cost, simple setup, and being immune to environmental effects. Despite that, the translation of the vision-based inspection to in-service structures in Vietnam has been limited so far. Herein, the authors examine the field applicability of a vision-based approach for joints monitoring of a historical truss bridge in Vietnam. Firstly, a well-established vision-based bolt-loosening monitoring approach is briefly described. Secondly, a field test on the Nam O bridge (Da Nang City) is performed. A digital camera is used to capture the images of representative bolted joints of the bridge. Lastly, the vision-based approach is applied to monitor the bolted joints. The angle of bolts in the joints is estimated from the captured images, from which the accuracy of the approach is evaluated. This study is one of the first case applications, demonstrating the field applicability of the vision-based bolt-loosening approach for inspecting a real bridge in Vietnam.

Keywords: bridge monitoring, vision-based inspection, bolted joint, loosened bolt detection, structural health monitoring, damage detection.

1. INTRODUCTION

Bolted joints are important links in steel structures such as truss bridges, box girder bridges, frame buildings, wind turbine towers, etc. Loosened joints often carry risks leading to the failure of a structural system. Detecting loosened bolts in critical bolted joints is a well-established topic but very challenging for realistic large connections that often contain hundreds of bolts [1–5].

Visual inspection by a human is the simplest method for loosened bolt detection; however, the method is less sensitive to small damage sizes of bolts and also requires professional experiences of the inspector to obtain a certain accuracy. Researchers have developed sensor-based approaches which offer a higher sensitivity to minor damage [6–10]. However, the sensor-based approaches often need high-performance data acquisition systems in addition to many sensors and measurement channels to monitor a large joint. More importantly, the sensor's signals are significantly affected by environmental changes such as humidity and temperature, that often leads to false detections as well as sensor defects.

Recently, the vision-based approach has been studied by structural health monitoring and maintenance crews and emerged as one of the innovative inspection tools [11–13]. The vision-based approach is based on the use of images/videos obtained from digital cameras to characterize the structural integrity and identify structural damage. As compared with the conventional sensor-based inspection, the vision-based approach offers various unique advantages, such as non-contact sensing, low cost, simple setup and operation, a capability with monitoring large structures, and immune to temperature changes. Besides, the vision-based method still has some limitations. The quality of images can be influenced by various factors, such as the vibration of cameras, the variation of lighting conditions, and fog.

Several vision-based loosened bolt detection approaches have been developed by several research groups. The first vision-based method for loosened bolt detection which integrates various image processing techniques was proposed by Park et al. (2015) [14]. This method is robust with minor looseness, but its performance is mainly dependent on the clearness of bolt tips in the connection image. Nguyen et al. (2016) [15] modified Park's method with the inclusion of a perspective correction step for enhancing bolt-loosening detectability under arbitrary shooting views. Ramana et al. (2018) developed a vision-based method integrating the Viola-Jones algorithm with support vector machines [16]; the Viola-Jones algorithm is used to recognize bolts in the connection image and the support vector machines are used to classify loosened bolts based on extracted dimensional parameters of the bolts [16]. Kong et al. (2018) proposed an idea to register and align two bolted joint images before and after bolt-loosening through image registration processes for loosened bolt detection [17]; the method shows promising performance, but it requires similar camera poses and shooting conditions between two inspection periods to ensure good performance.

Recent success in deep learning has enhanced the robustness of the vision-based approach. Several vision-based deep learning methods have been proposed recently. Zhao et al. (2019) trained a deep learning model to track the rotation of the features on the bolt's surface [18]. Wang et al. (2019) developed a vision-based method for flange connections with aids of deep learning and image processing techniques [19]. Nonetheless, those methods are not suitable for monitoring large bolted connections which often consist of many bolts. Recently, a quasi-autonomous vision-based bolt-loosening detection method was developed and showed the promising capability of monitoring large-scale bolted connections [20,21]. The method uses a regional convolutional neural network (RCNN)-based deep learning model for automated detection of numerous bolts in a connection image and robust image processing techniques to estimate the rotation of detected bolts. Despite the previous investigations, there exists only limited research on the field application of the vision-based bolt looseness detection approaches for realistic large-scale structures.

To the best of our knowledge, researches on vision-based approaches for loosened bolt detection have been limited in Vietnam so far. This study is motivated to examine the applicability of the integrated RCNN-image processing method for monitoring large-scale bolted joints of a realistic bridge in Vietnam. To obtain the objective, the following approaches are performed. Firstly, the bolt-loosening monitoring approach based on integrated RCNN-image processing is briefly described. Secondly, field experiments on a historical truss bridge, the Nam O bridge in Da Nang City, is performed. A digital camera is used to capture the images of representative bolted joints of the bridge. Lastly, the vision-based approach is applied to monitor the bolted joints. The rotations of the bolts in the joints are estimated from the captured images, from which the accuracy of the approach is evaluated.

2. VISION-BASED BOLT LOOSENESS DETECTION METHOD

In this investigation, the authors selected a well-established vision-based bolt looseness detection method, which combines the deep learning technology with image processing [20]. This is because the integrated deep learning-image processing method is particularly suitable for assessing the structural condition of large-scale bolted joints. In the following, we briefly describe the method; detailed descriptions can be found in reference [20].

Overall, the methodology is accomplished in 3 steps (see Fig. 1). In Step 1, images of a bolted connection are captured by a digital camera. The higher resolution of bolts will result in better estimation of bolt rotations. In Step 2, the captured images are put in a developed deep learning model for automatic bolt detection, and the angles of detected bolts are automatically estimated by several image processing techniques. The RCNN-based bolt detector is used for bolt detection, as described in Section 2.1. The perspective distortion of the image is corrected by a homography-based algorithm, as described in Section 2.2. The Hough transform and the Canny edge detector are used to estimate the bolt angle, as described in Section 2.3. In Step 3, loosened bolts are automatically identified by computing the bolt-rotation angles and comparing them with a defined threshold. If the rotational angle of a bolt is above the threshold, that bolt is classified as 'loosened', otherwise, it is 'tightened'. The loosening size of loosened bolts is also quantitatively estimated. It is noted that the later investigation only focuses on Step 1 and Step 2 of the process because long-term monitoring to detect any rotated bolts in Step 3 is under investigating.

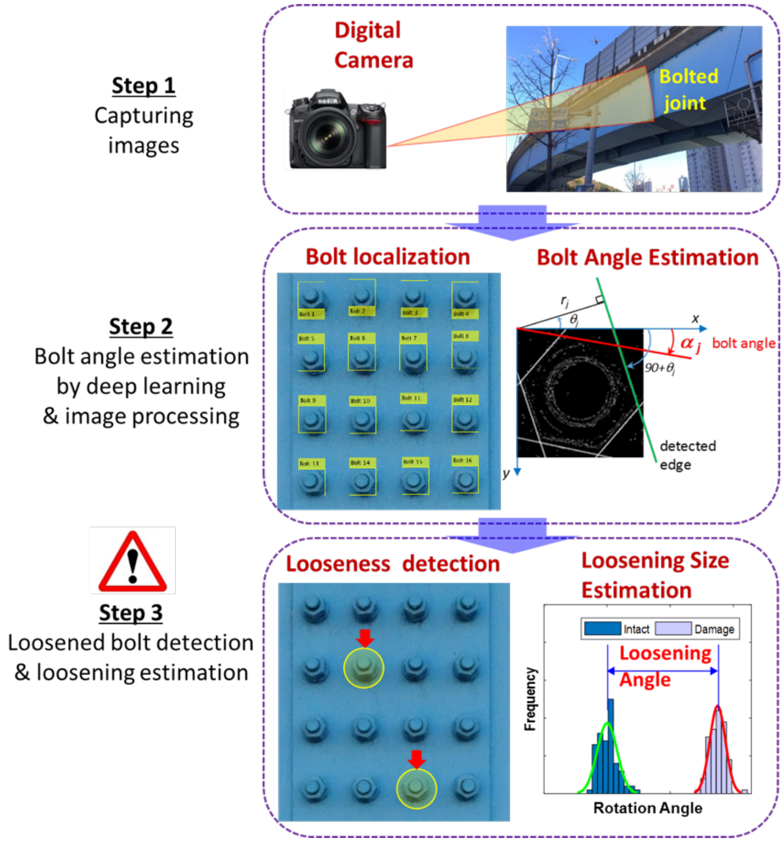


Fig. 1. Vision-based bolt-loosening detection method

2.1. Bolt detection approach

The deep learning-based bolt detector is based on the RCNN model, as sketched in Fig. 2. The detector has four major steps: (a) to take the input image; (b) to extract object proposals using the selective search algorithm; (c) to compute the feature vectors of each extracted object proposal using a convolutional neural network (CNN) model; (d) to classify the extracted object proposals into 'bolt' or 'not bolt' (background).

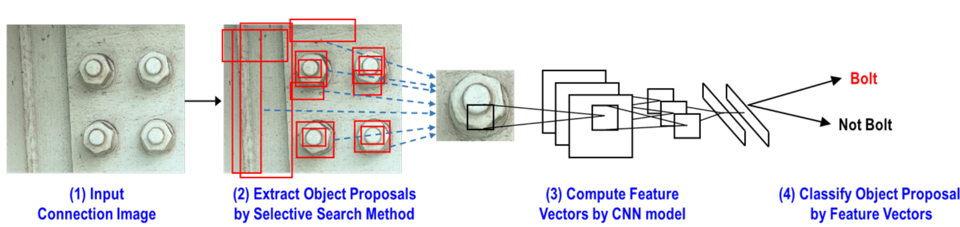


Fig. 2. Bolt detector using RCNN model [20]

The selective search algorithm is used to provide regional proposals, which are potentially detecting objects, for the CNN model. The principal idea of the selective search algorithm is to generate initial numerous regions from the input image and then form a larger region based on the feature similarities [22]. The principal of the selective search algorithm can be found in reference [23].

The CNN model is developed to compute the feature vectors for bolt classification. The CNN model used in this study follows the model in [20]. The network has 15 layers, which are constructed from basic layers: input, convolution, max pooling, fully connected, softmax, output. The CNN layers and their operators are described in Tab. 1. Each layer is activated by an operator which activates certain features of the detecting object. Those layers are configured to sufficiently extract the feature vectors, which is a dense representation of an object proposal. The RCNN model was trained on a realistic databank and achieved an accuracy of 99.22% after 5000 iterations. The descriptions of the RCNN model and its training process are detailed in the previous publication [20].

Table 1. Description of the CNN layers and operators [20]

Layer's ID	Size	Operator	Size	Number	Stride	Padding
L1	32×32×3	Input	-	-	-	-
L2	32×32×32	Conv	5×5×3	32	1	2
L3	15×15×32	MaxPool	3×3	-	2	0
L4	15×15×32	ReLU	-	-	-	-
L5	15×15×32	Conv	5×5×3	32	1	2
L6	15×15×32	ReLU	-	-	-	-
L7	7×7×32	MaxPool	3×3	-	2	0
L8	7×7×64	Conv	5×5×3	64	1	2
L9	7×7×64	ReLU	-	-	-	-
L10	3×3×64	MaxPool	3×3	-	2	0
L11	1×1×64	FC	3×3×64	64	-	-
L12	1×1×64	ReLU	-	-	-	-
L13	1×1×2	FC	1×1×64	2	-	-
L14	1×1×2	Softmax	-	-	-	-
L15	1×1×2	Output	-	-	-	-

2.2. Perspective rectification approach

Connection images are often captured under a certain level of perspective distortion. Thus, it is necessary to rectify the shooting perspective for an accurate bolt looseness estimation. For that purpose, the homography-based perspective rectification approach is adopted [15, 24]. The method is based on a projective transformation (i.e., the homography) with the use of homogeneous coordinate systems to transform an image from the image plane into the world plane. Given a homography matrix $\mathbf{H}$, a point in the image plane $p_j = (u_j, v_j, 1)$ can be transformed to a point in the world plane $q_j = (x_j, y_j, 1)$, as follows

$$p_j = \mathbf{H}q_j \quad \text{where} \quad \mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \tag{1}$$

in which u_j and v_j are the horizontal and vertical coordinates of p_j; x_j and y_j are the horizontal and vertical coordinates of q_j; $h_{11}, h_{12}, h_{13}, h_{21}, h_{22}, h_{23}, h_{31}, h_{32}$ are 8 elements of the matrix $\mathbf{H}$, representing 8 projective transformations (i.e., 3-axis rotation, 3-axis translation, and 2-axis scaling transformations).

To perform the projective transformation, it is essential to determine the matrix $\mathbf{H}$. To obtain the matrix $\mathbf{H}$, four points in the reference image and those in the distorted image should be determined. Herein, the centres of the four corner bolts detected by the bolt detector are used. By using the coordinates of the four points pairs, p_j and q_j ($j = 1 : 4$), which are identified from the distorted image and the reference image, the components of the homography matrix $\mathbf{H}$ can be obtained based on Eq. (1). After that, all points in the distorted image can be transformed to the points in the new image. More detailed information of the homography-based perspective correction algorithm can be found in [20].

2.3. Bolt looseness detection approach

The bolt looseness detection approach for hexagon bolts is described. Hough transform is performed on the image of a detected bolt to detect nut edges and to estimate the bolt angle. The Hough transform algorithm has four main steps: (a) the Canny edge detection is performed on the cropped image to detect the bolt's edges [25]; (b) the points of the detected edges are mapped to the Hough space and stored in an accumulator; (c) the true edges of the bolt are extracted from the accumulator by defining a threshold; and finally (d) the extracted edges are sketched on the cropped image and their equations are extracted for bolt angle estimation.

It is supposed that the j^{th} true edge of the bolt, detected by the Hough transform, is described by the two parameters (θ_j, r_j), as described in Fig. 3. Thus, the angle of the j^{th} edge is defined as $\theta_j + 90^\circ$, which is the angle between the j^{th} edge and the horizontal direction. Due to the inborn shape of the hexagon bolt, the angle of the j^{th} edge can be consistently expressed in the range of $0^\circ - 60^\circ$ as

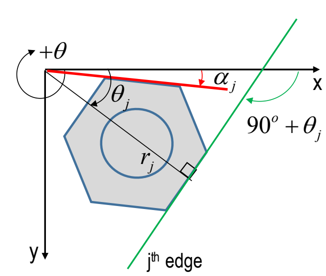


Fig. 3. Estimation method of bolt angle

$$\alpha_j = \text{mod}\left[(\theta_j + 90^\circ)/60^\circ\right] \tag{2}$$

in which α_j is the equivalent angle of the j^{th} edge and should be the same for all edges (see Fig. 3); mod[.] is the remainder of a division. To consider all true edges of a bolt, the angles are averaged as

$$\alpha = \frac{1}{k}\sum_{j=1}^{k} \alpha_j \tag{3}$$

where α is the bolt angle, and k is the number of selected bolt edges. It is noted that $k \leq 6$ should be preset in practice.

The rotational angle of the bolt ($\Delta\alpha$) is estimated by comparing the present angle with the one obtained in the intact state. For detecting loosened bolts in the connection, the absolute rotational angle $|\Delta\alpha|$ is often compared with a control limit. The bolt is 'loosened' if the rotational angle is higher than the threshold; otherwise, the bolt is 'tightened'. A well-established control limit is determined by three standard deviations of the mean with a confidence level of 99.7%.

3. VISION-BASED INSPECTION OF BOLTED JOINTS OF A HISTORICAL TRUSS BRIDGE IN VIETNAM

3.1. Experiments on historical truss bridge

The test bridge is a historical truss bridge, the Nam O Bridge in Da Nang City (Vietnam). The bridge crosses Cu De River and is an important link in the national high way 1A of Vietnam, as shown in Fig. 4(a). The bridge has four spans and each span consists of many large bolted joints, as shown in Fig. 4(b). The bridge was constructed before 1975, the year of the reunification of Vietnam. So far, the bridge has been maintained several times and its current structural performance is an important concern. Health monitoring of the old bolted joints of the bridge is essential to ensure their safety and serviceability.

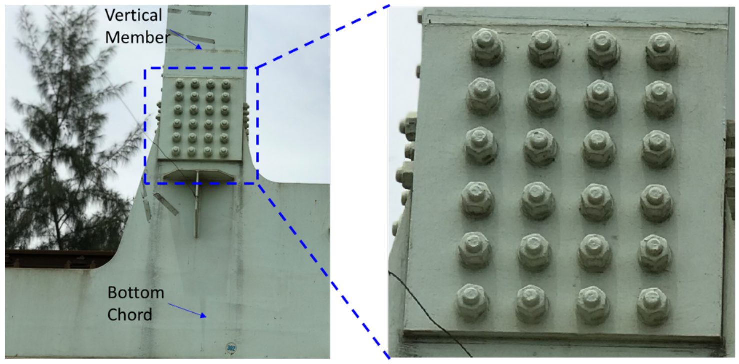
(a) Location of the Nam O Bridge (obtained from Google Maps)

(b) Real view of the Nam O bridge

Fig. 4. Nam O Bridge in Da Nang City, Vietnam

In this study, the authors used a digital camera to shoot the images of several bolted connections (a resolution of 4032×3024 pixels, AF f/2.8, a focal length of 7 mm). The connection images were input into the vision-based approach for bolt-loosening monitoring. Fig. 5 shows the selected images of two bolted joints of the bridge. As shown in Fig. 5(a), the first one is the joint between the vertical member and the bottom chord of the bridge, which has 24 bolts. The second one is the joint between the floor beam and the stringer of the bridge, which also consist of many bolts, see Fig. 5(b).

It is noted that both joint images have certain levels of perspective distortion, which should be corrected to enhance the accuracy of bolt angle estimation. In the following, the bolts in those connections are detected and their angles are estimated by the vision-based



(a) A joint of the vertical and bottom chord

(b) A joint of the floor beam and stringer

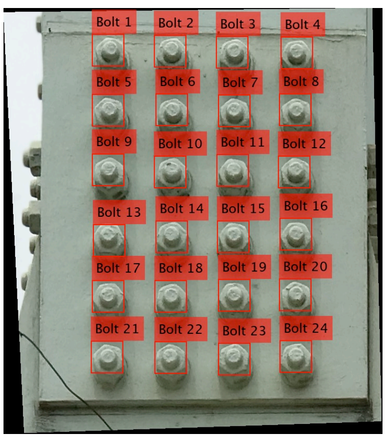
Fig. 5. Images of a representative bolted joint of Nam O Bridge

approach through the deep learning-image processing integration. A programming platform, Matlab 2020a, was used to build the RCNN model and to conduct all computations in this study.

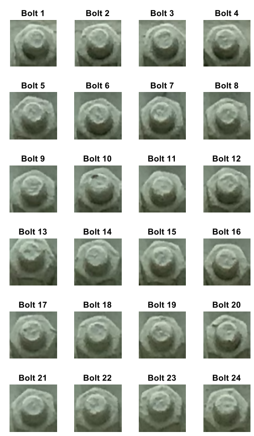
3.2. Vision-based bolt-angle estimation: Vertical member-bottom chord joint

The results of bolt detection and bolt angle estimation of the vertical member-bottom chord joint by the vision-based approach are presented in Fig. 6. It is shown in Fig. 6(a) that the perspective distortion of the joint image was corrected by the homography algorithm [20] and all 24 bolts of the joint were successfully detected by the deep learning-based bolt detector. After bolt detection, the detected bolts were labelled from Bolts 1 to Bolt 24. The labelling rule is based on sorting the bolts' coordinates from left to right and top to bottom. The detected bolts were subsequently cropped in sub-images of single bolts, as displayed in Fig. 6(b).

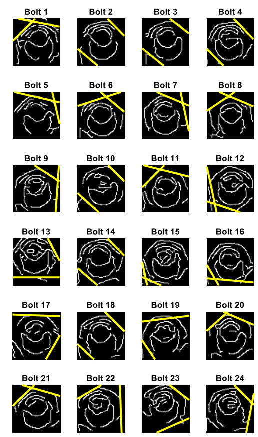
Afterwards, the angles of the bolts were estimated by the Hough transform algorithm. As shown in Fig. 6(c), two strongest edges of Bolts 1- Bolt 24 were well identified ($k = 2$). Basically, all six edges of a bolt should be used for angle estimation. Nonetheless, it is hard to capture the six edges of all bolts in a realistic joint, as evidenced in Fig. 6(c). Fig. 6(d) shows the comparison of the estimated angles of the bolts between the vision-based approach and the manual measurement by a protractor. There exists strong consistency between the two methods (99.3% correlation) in which the estimated bolt angles by the vision approach are well-agreed with the measured ones by the protractor. The result evidenced the reliability of the vision-based approach for monitoring large connections in the field.



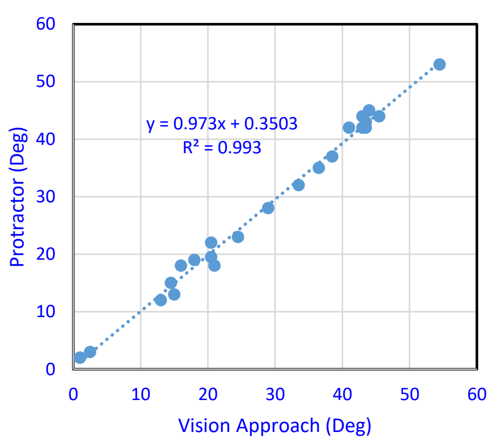
(a) Perspective correction and bolt detection



(b) Bolt segmentation



(c) Bolt angle estimation

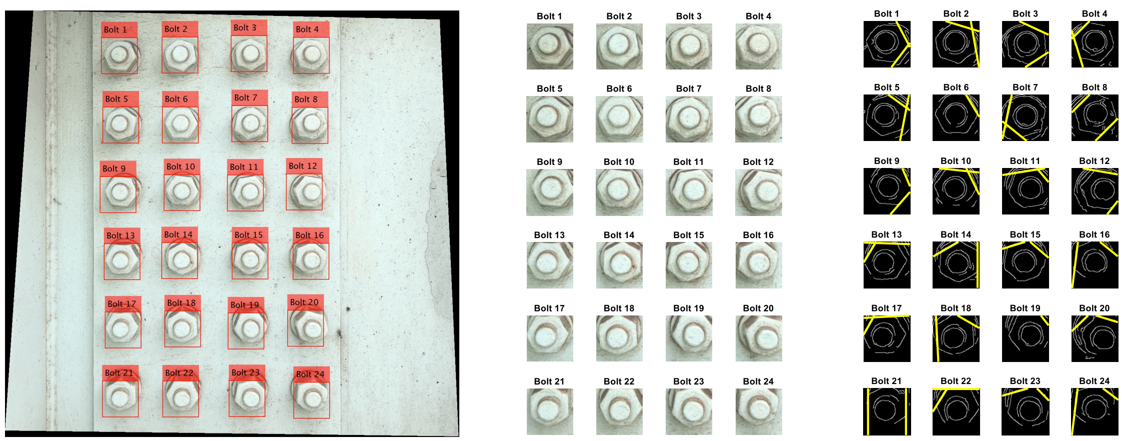


(d) Accuracy of vision approach

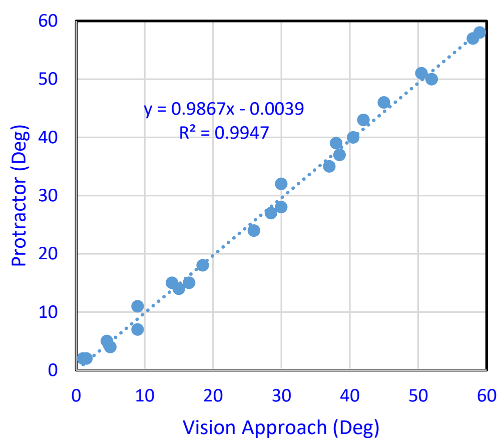
Fig. 6. Bolt angle estimation for the joint of vertical member and bottom chord

3.3. Vision-based bolt-angle estimation: Floor beam-stringer joint

As the second example, the vision-based bolt detection and bolt angle estimation are conducted on the vertical member-bottom chord joint, as shown in Fig. 7. After the perspective distortion by the homography method, all bolts of the joint were successfully identified by the bolt detector, as depicted in Fig. 7(a). The detected bolts were then labelled by Bolts 1 - Bolt 24 and the detected bolts were cropped in sub-images of single bolts, as seen in Fig. 7(b). Lastly, the bolt angles were estimated by the Hough transform algorithm [20]. Two strongest edges of Bolts 1- Bolt 24 were well identified, as shown in Fig. 7(c).



(a) Perspective correction and bolt detection (b) Bolt segmentation (c) Bolt angle estimation



(d) Accuracy of vision-based approach

Fig. 7. Bolt angle estimation for the joint of floor beam and stringer

For the accuracy evaluation, the comparison between the vision-based bolt angle estimation and the measurement by a protractor is shown in Fig. 7(d). The protractor-based method is a kind of visual inspection by the human. This method is labour-intensive and dangerous in some situations. However, it is simple to perform do not require high computational costs. The bolt angle estimation results between the two methods were well-agreed with a high correlation of 99.5%. This result again proved the accuracy of the vision-based approach for inspecting realistic bridge joints in practice.

4. SUMMARY, CONCLUSION, AND FUTURE WORK

This study examined the applicability of the RCNN-image processing integrated method for monitoring large-scale bolted joints of a realistic bridge in Vietnam. Firstly, the vision-based bolt-loosening monitoring approach was briefly described. Secondly, field experiments on a historical truss bridge, the Nam O bridge in Da Nang City, was performed. A digital camera was used to capture the images of representative bolted joints of the bridge. Lastly, the vision-based approach was applied to estimate the bolt angles of the two representative joints (i.e., the vertical-bottom chord joint and the floor beam-stringer joint) of the test bridge.

The bolt angles estimated by the vision approach showed a good agreement with the manual measurement by protractor, showing the potentials of the vision-based approach for inspecting realistic bridge connections in the field. So far, there exists limited research on vision-based approaches for loosened bolt detection in Vietnam. As the safety of historical bridges is increasingly concerned, this study could provide practical value for structural health monitoring practices of aging truss and girder bridges in Vietnam.

Nonetheless, to ensure the in-service strength of the bolted joints of the test bridge, it is necessary to capture the joint images and monitor the rotations of bolts over time. The long-term monitoring of the bridge joints by the vision-based approach is under investigating and will be presented in future work. The effect of the light condition, the distance from the camera to the joint, the specification of the camera on the image quality and detection results will be also investigated in details.

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